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AN EXPERIMENTAL METHOD FOR PREDICTING PLANT YIELD RESPONSE TO POLLUTION TIME SERIES

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Abstract—The purpose of this research is to formulate an experimental method which can predict yield loss of crops grown under naturally varying sulfur dioxide concentrations.

A model for simulating realistic fluctuations in SO_2 air pollution is developed. This model is used to define an experimental method, using exposure chambers, which can establish functional and probabilistical relationships between yield loss and median SO_2 concentration. This stochastic experimental design is offered as a viable alternative to traditional long-term fixed concentration experiments.

1. INTRODUCTION

A fundamental problem in air pollution-plant effects research is to predict reduction in yield of crops grown in areas of significant SO_2 stress. Within such areas pollutant concentration at any point in time is only probabilistically predictable. Assuming SO_2 source strength in an area does not vary over time, then fluctuations in pollutant concentration are caused primarily by random variations in wind speed. Pollutant time series for different growing seasons appear to be considerably different but they are probabilistically the same. Because of this probabilistical regularity, a model with a maximum of two or three parameters can simulate certain pollutant time series. It is our purpose in this paper to motivate the use of a time series model for experimentally studying the effect on plant yield of stochastically varying pollutant concentrations.

Plant growth rate fluctuates in correspondence with pollutant time series and yield is the integral, over a growing season, of the resulting growth rate time series. Hence yield in different growing seasons is probabilistically the same. Knowledge of a pollutant probability distribution should allow one to predict, for any growing season, the probability distribution of yield.

We have postulated a relationship between instantaneous growth rate and pollutant concentrations, but establishing this relationship is not trivial. It is not practical to continuously monitor growth rate in order to study its relationship with randomly varying pollutant concentrations. Even if it were possible to monitor growth rate it would be an exceedingly complex task to correlate it with observed fluctuations in pollutant concentration. To achieve a desirable precision, a model would have to consider response time lags, recovery rate at different concentrations, adaptation and of course variation in other environmental variables which affect growth rate.

Since we cannot construct a model which will predict growth rate as a function of pollutant concentration and environmental variation we might ask whether there exists a summary statistic for a pollutant time series which would correlate well with plant yield. It is the objective of this paper to suggest an experimental approach which can be used to define the relationship between yield response and summary statistics for a pollutant time series.

One experimental technique which has been used to estimate the effect of SO_2 on crop yield is the "long-term fixed concentration experiment." Plants are subjected to a fixed SO_2 concentration for an entire growing season. The critical assumption underlying this approach is that reductions in yield would be the same as if the pollutant concentration had varied stochastically about an average equal to the experimentally fixed concentration. Since this type of experiment ignores interactions between growth rate and pollutant concentration we suggest abandoning it in favor of experiments which expose plants to realistic pollutant time series over an entire growing season. Final yield of plants would then be correlated with summary statistics which characterize the entire pollutant regime to which plants were exposed.

This strategy has led to at least three different experimental methods which appear promising. Oshima *et al.* (1976) conducted growth experiments based on environmental gradient analysis. In this design, crops are grown in identical field plots maintained at different distances from a strong urban oxidant source, thus providing a natural gradient in average concentration and dose. A second method is the zonal air pollution system (ZAPS), described by Lee *et al.* (1975). The system employs grids of pipes that dispense gaseous pollutants on field plots. Source strength is varied over several plots to create a gradient of average concentrations, and local variations in wind speed produce realistic short-term fluctuations in concentration.

A third approach, described here, uses exposure chambers to control the SO_2 regime. Pollutant concentrations in chambers are changed periodically so that plants are exposed to a pollutant time series. This flexibility provides a distinct advantage over the natural gradient and ZAPS methods which depend on local meteorological conditions for concentration variability.

This approach is sensible only if one can quantitatively summarize long, continuously-changing time series of pollutant concentrations. Fortunately, traditional statistical analyses (Larsen, 1971) coupled with advances in time series analysis techniques (Box and Jenkins, 1976; Jenkins and Watts, 1968) satisfy this need. This paper describes a model which will generate realistic pollutant time series and discusses the design of plant yield studies based on this model.

2. CHARACTERISTICS OF POLLUTANT TIME SERIES

The standard method of summarizing concentration levels observed over a long time interval is to plot their relative frequencies of occurrence. Typically the data consists of low concentrations with infrequent occurrences of high concentrations. The frequency curves can usually be described by a lognormal distribution over a broad range of pollutant types and source configurations (Larsen, 1971; Lee *et al.*, 1975; Gifford, 1974; Bencala and Seinfeld, 1976). Gifford (1974) and Knox and Pollack (1974) provide a simple theoretical explanation of the observed lognormality. They argue that a pollutant from several sources, as seen in urban areas, tends to have concentration levels which are highly correlated over short time intervals, and they show how this leads to a lognormal frequency curve.

If concentrations are distributed lognormally, they can be characterized by a median and shape parameter. It is, therefore, sufficient to correlate plant response with these parameters of the distribution.

A common test for lognormality is to see whether the empirical distribution function plots as a straight line on logarithmic-probability paper. The Air Quality Criteria for Sulfur Oxides (1970) shows the empirical distribution functions for SO_2 concentration for six large cities across the United States (Continuous Air Monitoring Project [CAMP], 1962–1967, 1-h averaging time). These distributions, plotted on logarithmic-probability paper, range from slightly curved to approximately straight lines. A general impression is that they could be approximately modeled as a family of parallel straight lines. This is equivalent to saying that the concentrations are lognormally distributed with a common shape parameter but with varying medians.

A possible explanation for this phenomenon is that the shape parameter is determined by meteorological factors independently of source strength of the pollutant while the median is determined primarily by source strength. This explanation is supported empirically by studies with the Zonal Air Pollution Study (Lee *et al.*, 1975).

Concentration series are highly correlated over short time intervals. If the median and shape parameter of the concentration distribution stay constant over the growing season, then the degree of autocorrelation can be specified by one parameter.

3. TIME SERIES MODEL

To perform a controlled time series experiment, a model must be used to generate exposure schedules. Varying levels of realism can be incorporated into this model. The first step in constructing the model is to decide what features of a natural time series are important for simulation. In the previous section we summarized the properties of natural pollutant time series. We must now model these properties with a set of mathematical assumptions. The criteria which are important for a pollutant time series model are:

(1) lognormally distributed concentrations;
(2) stationarity, i.e. the distribution of concentration is time invariant;
(3) autoregressive, i.e. future concentrations depend upon past behavior and
(4) realistic autocorrelation function, i.e. similar to the natural time series reported in Pollack (1973) and Barlow and Singpurwalla (1974).

A preliminary discussion of the lognormal distribution and auto correlation functions will simplify presentation of the stochastic model.

The lognormal distribution, $\mathrm{LN}(m, \sigma)$, with median, m, and shape parameter, σ, has a distribution function given by

$$\mathrm{LN}(c; m, \sigma) = \int_0^c \frac{1}{\sigma y \sqrt{2\pi}} \exp\left(-\tfrac{1}{2}[(\ln y - \ln m)/\sigma]^2\right) dy.$$

The natural logarithm of a lognormal random variable has a normal distribution with mean $\ln m$ and standard deviation σ, i.e. if $C \sim \mathrm{LN}(m, \sigma)$ then $\ln C \sim N(\ln m, \sigma)$. This property allows the parameters of the lognormal to be estimated from data using standard statistics for the mean and standard deviation. The median is estimated by the geometric mean of the data and the shape parameter is estimated by the standard deviation of the logarithms of the data.

The correlation function of a stationary stochastic process, $\{C(t), t = 1, 2, \ldots\}$, measures the correlation between occurrences which are h time units apart. For a given lag time, h, it is defined as

$$\rho(h) = \frac{E[C(t)-\mu][C(t+h)-\mu]}{E[C(t)-\mu]^2}$$

where $\mu = EC(t)$ is the mean value of the stochastic process.

Autocorrelation functions of natural pollutant time series are characterized by high correlations for small

lag times and decreasing dependence with larger lag times. Certain periodic human activities cause spikes at daily and weekly lag times.

A stochastic model which satisfies our four criteria can be expressed in terms of the two parameters of the lognormal distribution, m and σ, and a third parameter, λ, called the autocorrelation parameter. We will assume that the concentration $C(t)$ depends only on the immediate past value, $C(t-1)$, and a random shock. Such a model is called a first-order, autoregressive, stochastic process. The concentration at time t is given in terms of the concentration at time $t-1$ by

$$C(t) = m\left[\frac{C(t-1)}{m}\right]^{\lambda} Z(t) \quad (0 < \lambda < 1),\ t = 1, 2 \ldots. \tag{1}$$

In this model $Z(t)$, $t = 1, 2, \ldots$ are independent, lognormally distributed random variables with median equal to one and shape parameter equal to $\sigma\sqrt{1-\lambda^2}$, i.e.

$$Z(t) \sim \ln(1, \sigma\sqrt{1-\lambda^2}). \tag{1a}$$

Concentrations less than the median occur half of the time and concentrations higher than the median occur half the time, but the frequency at which low and high concentrations occur is determined by the shape parameter, σ. Varying the median concentration corresponds to varying the source strength of a diffuse source, while varying the shape parameter corresponds to varying meteorological conditions. Monitoring data taken from widely separated locations show surprisingly small variation in the shape parameter (Larsen, 1971). However, small variations in σ could be extremely important to plants because of its effect on the frequency of high concentrations.

The parameter, λ, determines the degree of dependence of $C(t)$ on previous concentrations $C(t-1)$, $C(t-2), \ldots$. Varying the correlation parameter, λ, changes the time behavior of the process. With a small value of λ a strip chart of concentration vs time would look like a comb, while a large value of λ would cause the strip chart to look more like hills and valleys.

The autocorrelation function of this stochastic process at lag h is given by

$$\rho(h) = \frac{\exp(\sigma^2\lambda^h) - 1}{\exp(\sigma^2) - 1} \quad h > 0, \qquad 0 < \lambda < 1. \tag{2}$$

It is a decreasing function of lag time and for appropriate choices of λ and σ it approximates the sample autocorrelation functions found by Pollack (1973) and Barlow and Singpurwalla (1974). When the autocorrelation parameter, λ, equals zero, the autocorrelation function is always zero and the process is completely random with respect to time. When $\lambda = 1$ the autocorrelation function is always one, the variables $Z(t)$ become one (see Equation 1a), and the process is completely determined in time.

As long as $0 < \lambda < 1$, the concentrations generated by (1) will be lognormally distributed with median m and shape parameter σ.

A convenient method for generating exposure schedules is obtained by taking logarithms of (1); i.e.

$$\ln C(t) = \ln m + \lambda[\ln C(t-1) - \ln m] + \ln Z(t).$$

Since $\ln Z(t)$ is normally distributed with mean zero and standard deviation $\sigma\sqrt{1-\lambda^2}$ one can first generate the logarithm of the stochastic process, using a random normal deviate generator, and then exponentiate the result. To start the recursion, generate $\ln C(0)$ from a normal distribution with mean $\ln m$ and standard deviation σ.

4. EXPERIMENTAL DESIGN

The more closely experimental exposure schedules simulate the characteristics of natural variation in pollution concentration, the more confidence one will have in the resulting response curves as predictors of yield reduction. An experimental method will now be defined which relates plant yield to median SO_2 concentration. The resulting response curves are theoretically good predictors of yield associated with natural exposures to pollution.

The time series model presented in Section 3 is the basis for defining exposure schedules. Given a specified median, shape parameter and correlation parameter, a random time series can be generated using the method discussed in Section 3. A time resolution of one hour is probably sufficiently refined for annual yield experiments. The exposure schedule would be presented to plants grown in exposure chambers and a number of chambers would be required to define a response curve. If plants are grown in pots which can be moved, it is possible to define an experiment where each pot in the experiment experiences a different pollutant time series.

Stochastic models for exposure schedules introduce another dimension of replication into experimental designs. Any given stochastic treatment schedule is only one of an infinite number of time series which have the same statistics. Referring to the model defined in (1) a given treatment is specified by the parameters m, σ and λ. Equation (1) can be used to generate many time series which provide different schedules for replicate treatments. If plants were equally sensitive to an air pollutant at all times within a growing season then the average yield response to the different replicate time series would be the same. In this case, the relevant estimation problem is to experimentally vary the parameters m, σ and λ and describe the variation about a yield-response model. If plant sensitivity varies greatly over time, then the parameters, m, σ and λ might not correlate well with plant yield and some other statistic of the time series, such as the mean of a weighted average of plant sensitivity and the time series, might be appropriate.

The yield of a plant exposed to a randomly chosen time series has two inherent sources of variability; one attributed to the distribution of time series and the other attributed to other environmental variables and genetic effects. If a number of sample time series are used as exposure schedules for different plants then the average plant yield will estimate mean plant yield for an area characterized by an SO_2 time series with specified parameters. The larger the number of time series sampled the greater the precision of the estimate.

If instead of selecting a sample of time series each with the same median, a gradient in median concentration is used and a randon time series with each median is generated then we have the basis for a response curve experiment. Regression techniques can be used to estimate the response curve and the variability of the estimates.

Experimental designs incorporating gradients in the shape parameter and correlation parameter could also be designed but they would probably yield less valuable information. The shape parameter and correlation parameter of SO_2 time series are not related to source strength of SO_2 and they seem to vary little from place to place.

An n-hour-long time series generated by (1) is a random sample from an infinitely long time series with parameters m, σ and λ. The sample values $\hat{m}$, $\hat{s}$ and $\hat{\lambda}$ computed for different n-hour-long samples could vary greatly. If different plants are exposed for n hours to different sample time series drawn from the same parent time series, it is difficult to reason that they received the same treatment. If, however, the sampling is restricted so that each plant is exposed to an n-hour-long time series with the same sample values $\hat{\mu}$, $\hat{\sigma}$ and $\hat{\lambda}$, then the treatments are comparable.

An n-hour-long time series which has specified sample median, $\hat{m}$, and specified sample shape parameter, $\hat{\sigma}$, may be generated as follows:

(1) Using the time series model generate an n-hour-long time series using any values for the parameters that you desire.
(2) Calculate the sample median, g, and the sample shape parameter, s, of the generated time series.
(3) Calculate a transformed time series by transforming each value of the generated time series by the formula, $a[C(t)]^b$, where $b = \hat{\sigma}/s$ and $a = \hat{m}/g^b$.

The statistics g and s are calculated as

$$g = \exp\left[\frac{1}{n}\Sigma \ln C(t)\right]$$

$$s = \sqrt{\frac{1}{n}\Sigma[\ln C(t) - \ln g]^2}.$$

An n-hour-long time series which has a specified sample correlation parameter, $\hat{\lambda}$, is obtained by generating a sufficiently large number of n-hour-long time series using $\lambda = \hat{\lambda}$, computing the sample correlation parameter, q, for each of these time series, and then selecting the one for which the difference, $q - \hat{\lambda}$, is the smallest. The procedure for calculating the sample correlation parameter is more involved than for the sample median and sample shape parameter. First, the sample correlation function must be calculated by the equation

$$r(h) = \sum_{t}^{n-h} [C(t) - g][C(t+h) - g]/s^2)/(n-h).$$

Second, a nonlinear estimation procedure must use the sample correlation function to estimate the parameter λ in Equation (2). The estimate, q, obtained from this procedure is the sample correlation parameter.

Consider now a response curve design where the sample median concentration is experimentally varied along a gradient. Each exposure chamber represents a different random time series with a different sample median, but with the same sample values $\hat{\sigma}$ and $\hat{\lambda}$. Each exposure chamber would contain a number of pots containing from one to several plants. At periodic intervals, of say one week, pots would be rearranged among the exposure chambers in such a manner that each pot would experience a different time series for the entire growing season. Figure 1 demonstrates how different times series can be produced for each pot in an experiment. A single pot exposure schedule is determined by assigning it an exposure chamber for each week of the experiment. The example time series at the bottom of Fig. 1 is constructed from the top four by assigning chambers in the chronological order 4, 2, 1 and 3. With c chambers and an r-week-long growing season, r^c different pot time series can be generated.

Weekly rearrangement of pots among exposure chambers places an additional restriction upon the

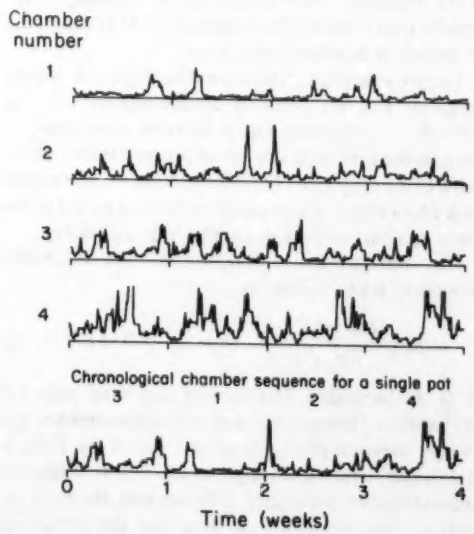

Fig. 1. Four-week-long pollutant time series within each of four chambers and an example exposure schedule constructed by moving a pot into different chambers during different weeks.

generated time series. The time series for a chamber must be composed of a sequence of one-week-long time series each with the same sample values $\hat{m}$, $\hat{\sigma}$ and $\hat{\lambda}$.

Our objective is to suggest a response curve design along a gradient in median SO_2 concentration where time series for different pots have the same sample values $\hat{\sigma}$ and $\hat{\lambda}$. These two criteria are conflicting. The sample shape parameter for a pot time series depends on differences among the logarithms of the weekly sample medians. If we want the sample shape parameters to be approximately constant, then we must restrict the range of medians. A further improvement upon the design allows us to satisfy both criteria.

Separate exposure chambers into several groups. Within a group, the range of the logarithms of the medians should be small. For all groups, the range of the logarithms of the medians should be approximately equal. Between groups, medians should be characterized by a range from low to high. Pots should only be rearranged within groups. Table 1 shows an example with 12 chambers separated into 3 groups. For this example, sample medians for pot time series will vary along a relatively continuous gradient from a low of 1.5 pphm to a high of 27.7 pphm. If pots are weekly rearranged within groups, the sample values $\hat{\sigma}$ and $\hat{\lambda}$ will remain approximately the same for each pot time series. For SO_2 experiments using a time resolution of 1-h, reasonable choices for the sample shape parameter and sample correlation parameter are $\hat{\sigma} = 0.89$ and $\hat{\lambda} = 0.9$.

Table 1. Experimental design with 12 chambers separated into 3 groups

Group	Median (pphm)	Logarithm of medians	Range of logarithms of medians
low	1.5	0.41	
	2.7	0.99	1.38
	3.4	1.22	
	6.0	1.79	
medium	3.5	1.25	
	6.2	1.82	1.31
	8.0	2.08	
	12.9	2.56	
high	7.1	1.96	
	12.4	2.52	1.36
	16.1	2.78	
	27.7	3.32	

If changing the concentration at hourly intervals during night time periods would be difficult or expensive, then the concentration could be kept constant at the average value of the time series for that period. Plants are typically less sensitive to SO_2 pollution at night when their photosynthetic mechanisms are shut down, so this plan would allow derivation of relatively unbiased response curves.

5. DISCUSSION

Economic loss in production, resulting from SO_2 air pollution, is the result of a continuous process of growth reduction over the life cycle of a species. Reduced harvest is usually not the result of a single episode of elevated SO_2 concentration but rather the cumulative effect of reduced growth rate over the whole growing season. In particular, growth rate at any time will depend upon the prevailing SO_2 concentration. Since SO_2 concentrations vary randomly, corresponding to fluctuations in wind velocity, exposure of plants to SO_2 pollution can only be expressed probabilistically. It is common practice to quantify the overall level of SO_2 pollution in an area by the median concentration computed over a year or some other sufficiently long period of time. It seems reasonable then that plant yield in an area would be related to median SO_2 concentration. If a function could be defined which gave plant yield reduction, for a species, as a function of median SO_2 concentration, then this function would be valuable in many applications.

In many areas where SO_2 air pollution is a problem, or is suspected to be a problem, there exists a monitoring program to track time series of concentrations. Within such areas yield response curves would be immediately applicable for predicting yield reductions and for providing a basis for economic assessment. In addition, regional air pollution models output characteristics of pollutant distributions, such as median concentration. This opens the possibility for relating source strength of SO_2 to economic loss through the chain of events: monitoring program – regional air pollution model – growth response curve – economic model. If growth response curves were available for a variety of agricultural crops it would be possible to compare their sensitivity to SO_2 pollution and even recommend crops which could be cultivated successfully in areas of elevated SO_2 pollution.

The stochastic model developed here is a good descriptor of natural concentration time series from diffuse sources, such as urban locations. It is not clear that the model is useful in simulating levels from a single point source such as a power plant in rural areas. There are few long-term studies of time series from a point source. Gifford (1974) has suggested, on empirical grounds, that a negative exponential provides the best fit to point source data and Knox and Pollack (1974) argue theoretically that the distribution is Chi Square with two degrees of freedom. The most probable concentration near a point source is zero, and high levels of pollutant are rare and unpredictable.

Exposure schedules which simulate a point source raise problems of replication and prediction of response. Imagine a concentration time series, the length of a growing season, which is dominated by zero levels and has only two or three concentration spikes high enough to affect plant growth. The problem is that plant growth response to such a schedule may vary widely, depending on timing of the spikes relative to each other and relative to developmental stages of a plant.

In summary, stochastic experiments provide a viable

alternative to long-term fixed concentration experiments for predicting crop losses caused by SO_2 air pollution. The probabilistic nature of SO_2 time series are fairly well understood and a model which will reasonably simulate realistic exposures has been suggested. Parameters of this model can be varied in exposure chambers to establish their correlation with crop yield. By designing the experiment so that a large number of different time series from the same model are tested then relatively precise probabilistic predictions of crop losses are possible.

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